

Time-Series Panel Analysis (TSPA) – Multivariate modeling of temporal associations in
psychotherapy process.

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Abstract

Objective: Processes occurring in the course of psychotherapy are characterized by the simple fact that they unfold in time and that the multiple factors engaged in change processes vary highly between individuals (idiographic phenomena). Previous research, however, has neglected the temporal perspective by its traditional focus on static phenomena, which were mainly assessed at the group level (nomothetic phenomena). To support a temporal approach, the authors introduce Time Series Panel Analysis (TSPA), a statistical methodology explicitly focusing on the quantification of temporal, session-to-session, aspects of change in psychotherapy. TSPA-models are initially built at the level of individuals, and are subsequently aggregated at the group level, thus allowing the exploration of prototypical models. **Method:** TSPA is based on vector autoregression (VAR), an extension of univariate autoregression models to multivariate time-series data. The application of TSPA is demonstrated in a sample of 87 outpatient psychotherapy patients that were monitored by post-session questionnaires. Prototypical mechanisms of change were derived from the aggregation of individual multivariate models of psychotherapy process. In a second step, the associations between mechanisms of change (TSPA) and pre-to-post symptom-change were explored. **Results:** TSPA allowed identifying a prototypical process pattern, where patient's alliance and self-efficacy were linked by a temporal feedback-loop. Furthermore, therapist's stability over time in both mastery- and clarification interventions was positively associated with better outcome. **Conclusions:** TSPA is a statistical tool that sheds new light on temporal mechanisms of change. Through this approach, clinicians may gain insight into prototypical patterns of change in psychotherapy.

Keywords: time-series panel analysis (TSPA); vector autoregression (VAR); mechanisms of change; psychotherapy process; self-efficacy

Time-Series Panel Analysis (TSPA) – Multivariate modeling of temporal associations in psychotherapy process.

When asked to describe the mechanisms of therapeutic change in a patient, a psychotherapist will likely point to associations between certain factors of the therapist-patient system. These associations occur temporally and in sequence: "When I did *X*, the patient responded *Y*". A therapist relies on highly idiographic information, temporal evolution, and the action of multiple factors when evaluating therapy effectiveness. Yet, comparing these properties of therapists' reasoning to the strategies predominant in psychotherapy research (such as outcome research, process research), a stark contrast exists between a therapist's real-life complexity and research-dictated simplicity. This paper aims to show that the viewpoints and interests of the practitioner and the scientist need not be mutually exclusive, and that time-series (i.e. repeated measurements) may capture the dynamics of a psychotherapy process and vastly broaden the analytic and inferential possibilities. We present statistical methodology that accounts for temporal and individual-level information (idiographic perspective) and also generates predictions at a general or group level (nomothetic perspective). In the following application of Time Series Panel Analysis (TSPA) to psychotherapy data, we will introduce the reader to a lesser-known methodology that is particularly well suited for the analysis of long time-series in psychotherapy research. Main advantages of TSPA are the following characteristics:

- Focus on the temporal aspect of psychotherapy
- Inclusion of multivariate associations
- Individual models (idiographic information)
- Prototypical models (aggregation of individual models to nomothetic models)
- Indices of (potential) causal associations between variables

Why do psychotherapy researchers profit from this methodology?

Outcome data have unquestionably demonstrated that psychotherapy works (e.g. Lambert & Ogles, 2004). Hence, during the past decade, the focus of psychotherapy research has shifted from efficacy studies to process studies. Consequently, effort is now being directed towards questions of why and how psychotherapeutic change is effective, but “... research studies have not equitably investigated all factors that either enhance or diminish psychotherapy effectiveness.” (American Psychological Association, 2012). Correspondingly, the TSPA approach to psychotherapy research is less concerned with the longstanding and ongoing controversy of common versus specific factors of psychotherapeutic change (Castonguay & Beutler, 2006; Chambless & Ollendick, 2001; DeRubeis, Brotman, & Gibbons, 2005; Pfammatter & Tschacher, 2012; Wampold, 2001), but directed at the multivariate influences and interdependencies between the active ingredients of psychotherapy. This view is in line with the additional questions of *why* (mediators of change), *for whom*, and *under what conditions* (moderators of change) change occurs (Laurenceau, Hayes, & Feldman, 2007). There is a growing literature on process dynamics in psychotherapy, studying time-varying factors that influence treatment progress and outcome (e.g. Hayes, Laurenceau, Feldman, Strauss, & Cardaciotto, 2007; Mahoney, 1991; Smits, Julian, Rosenfield, & Powers, 2012). While this topic is not new (Gottman & Rushe, 1993), it is gaining momentum with the availability of more sophisticated data analyses, either for the reanalysis of existing data (e.g. Fisher, Newman, & Molenaar, 2011), or for explorative studies on mechanisms of change (e.g. Tschacher, Zorn, & Ramseyer, 2012). We advocate the approach of TSPA (Tschacher & Ramseyer, 2009), a methodology focusing on the emergence of temporal dynamics between relevant factors of a psychotherapy system.

Background: Dynamic systems theory

The concepts of time and change are the fundamentals of dynamic systems theory, which addresses temporal dynamics and the formation and dissipation of patterns; both concepts are most relevant for psychotherapy research. The importance of the time dimension is readily evident in psychotherapy-process research, and the need or will for change is usually the reason why psychotherapy is initiated and conducted. Dynamic systems theory provides a mathematical background for the modeling of these phenomena, and self-organizational dynamics is a conceptual frame for the process of pattern formation. A process is termed self-organized when higher-order patterns spontaneously emerge from recursive interactions among simpler components. In the patient-therapist dyad, for example, seemingly unrelated processes may follow higher-order regularities which then give rise to new (emergent) qualities at the system level (Newell & Molenaar, 1998; Salvatore & Tschacher, 2012; Vallacher & Nowak, 1997; Vallacher, Coleman, Nowak, & Bui-Wrzosinska, 2010). A directly observable example for such a self-organized process is the synchronization of nonverbal movement between patient and therapist (Ramseyer & Tschacher, 2011). This kind of emergent processes was first described in synergetics (Haken, 1977), an interdisciplinary approach that explains pattern-formation and self-organization in open systems, i.e. systems that are open to external influences (= systems far from thermodynamic equilibrium). Self-organization is a pervasive phenomenon found in many domains such as motor behavior (Haken, Kelso, & Bunz, 1985), chemistry (Nicolis & Prigogine, 1977), biology (Kelso, 1995), and social interactions (Haken & Schiepek, 2006). Simply put, dynamic systems theory explicitly seeks to understand and describe the complexity of highly interdependent systems at a level of aggregation that usually goes beyond the abstraction found in traditional analyses. Dynamic systems theory is a 'structural science' that serves the purpose to provide the theoretical bases and concepts for more specific research endeavors, thus is

applicable to diverse research questions and scientific fields, including psychotherapy research (Fisher et al., 2011; Hayes & Strauss, 1998; Hayes et al., 2007; Laurenceau et al., 2007). For example, multivariate associations between time-series in psychotherapy have been investigated in post-session questionnaires (Tschacher & Ramseyer, 2009; Tschacher, Baur, & Grawe, 2000; Tschacher et al., 2012), treatments for social anxiety (Smits, Rosenfield, McDonald, & Telch, 2006), treatments for panic disorder (Meuret, Rosenfield, Seidel, Bhaskara, & Hofmann, 2010), in psychosocial crises (Tschacher & Jacobshagen, 2002), in symptom development in schizophrenic patients (Tschacher & Kupper, 2002), and in functional magnetic resonance imaging (Hamilton, Chen, Thomason, Schwartz, & Gotlib, 2011; Tschacher, Schildt, & Sander, 2010).

Ergodicity: Intraindividual models versus interindividual models

A further fundamental aspect that is explicitly addressed in TSPA is the concept of ergodicity (Molenaar & Campbell, 2009) – the question whether phenomena detected at the group level are related to the phenomena found at the level of the individual. Most psychotherapeutic research acts on the tacit assumption that assessments at the group level are representative for the individual level. Nomothetic evidence is treated as indicative of the idiographic level. This global stance may be challenged and there is growing evidence that ergodicity is the exception rather than the norm (Molenaar, 2004). For the current demonstration of TSPA, we honored the problem of ergodicity by assessing and modeling temporal relationships at the individual (idiographic) level (Collins, 2006; Curran & Bauer, 2011). In an independent step, we aggregated the models to assess a general (nomothetic) level to characterize the overall properties of the group (Hamaker, Dolan, & Molenaar, 2005).

Repeated measures in psychotherapy data

As outlined above, the goal of this paper is to demonstrate an efficient way of modeling temporal associations within and between repeatedly measured variables, so that the inherent dynamics can be quantified. The literature on such time-series data analysis has dramatically increased in the past decades (for reviews see e.g. Bollen & Curran, 2004; Collins, 2006; Raudenbush, 2001) and numerous procedures have been presented. The continued evolution and refinement of methods have also led to substantial overlaps: Previously distinct approaches – e.g. multilevel models [MLM] and structural equation models [SEM] – are integrated (e.g. Boker et al., 2011 [OpenMx]), thus differences have become less clearly distinguishable. In this paper, we will focus on Time Series Panel Analysis (TSPA), an extension of vector autoregression (VAR), which allows the multivariate modeling of relatively long series ($N > 20$) of repeated measurements, such as post-session questionnaires collected after each therapy session. TSPA uses VAR as the mathematical framework for the analysis of individual time series, and beyond the VAR analysis, TSPA aggregates and statistically tests for prototypical patterns present at the group level.

Key concepts of time-series analysis

Before detailing and comparing the various features of TSPA, we will first address the relevant basic concepts associated with time-series analysis. In Figure 1, two graphical representations of psychotherapy time-series (panels A & B) and their associated multivariate systems (panels C & D) are depicted. Five post-session questionnaire factors 'alliance patient', 'self-efficacy patient', 'alliance therapist', 'clarification interventions' and 'mastery interventions' are represented by different lines in the overlay plots (A & B) and by circles in the VAR models (C & D). The examples consist of psychotherapy systems that cover two time steps referred to as

$t-1$ (= previous session) and t (= today's session). The stepwise inclusion of temporal information (termed 'lags' in time-series analysis) determines the number of time steps that a time-series model 'looks back' in its analysis of associations between variables. The following central aspects are illustrated with numbers (1) to (7) in Figure 1:

-- Insert Figure 1 around here --

(1) Trends. Systematic shifts of average levels of a variable across time are called trends. In the case of psychotherapy data, most time series will show some kind of trend: Depending on the variable assessed, a trend may be positive as in the quality of the alliance, or negative as in the severity of symptoms. TSPA is focused on associations between variables over time irrespective of their overall trajectories. Therefore trends are mathematically accounted for prior to the analysis of such associations.

(2) Autoregression. A variable is said to have n autoregressive components [AR(n)] when the output of the variable linearly depends on its own previous values. The strength is quantified by ϕ (phi), which ranges between -1 and 1. In psychotherapy data, positive autoregression is usually found in variables that exhibit stability over time, such as e.g. the therapeutic alliance.

(3) Cross-regression. When multiple variables are simultaneously considered, their outputs may linearly depend on other variable's previous values. As in the case of autoregression, the strength of these cross-variable regressions is quantified by ϕ (phi). Positive values indicate positive associations while negative values denote inverse relationships. In a psychotherapy system, a patient's self-efficacy may e.g. be positively associated with his/her previous session's alliance.

(4) Synchronous associations. Whereas both auto- and cross-regression explicitly account for the temporal information in time series, synchronous associations designate the strength of the associations between two variables at identical points in time. They are calculated by Pearson correlations between the residuals of the VAR analysis. Using residuals has the effect of controlling for serial dependency (autoregression) as well as for cross-variable dependency (cross-regression). In psychotherapy systems, synchronous associations quantify how strongly e.g. alliance and self-efficacy are associated at the level of the same session.

(5) Causal inferences. Cross-regressions contain information pertaining to the question which change in a variable preceded change in another variable. The cross-regressions of VAR may be interpreted in a so-called quasi-causal way, because significant sequential associations reflect how a variable causally influences succeeding values of the other variable. In the time-series literature, this property is called Granger causality, where causality is derived from systematic time-lagged associations between two or more variables (Granger, 1969). In addition to Granger causality, causal mechanisms may be inferred using mediation analyses (for an overview, see Imai, Keele, Tingley, & Yamamoto, 2011). Such mediational causal inferences have been used in cross-lag panel analyses (Smits et al., 2006) and in structural equation models (e.g. Gates, Molenaar, Hillary, Ram, & Rovine, 2010). The discussion of different theoretical causality models is beyond the scope of this paper, a discussion of contemporary models of causality may be found elsewhere (Imai, Keele, & Tingley, 2010). To summarize, the question whether a specific predictive relationship does or does not imply causality cannot be determined statistically, but has to be decided based on current theoretical and empirical knowledge. In VAR, statistical tests to assess the strength of (putative) causal relationships are available (see supplementary online material, Tables W4 & W5).

(6) Idiographic model. When assessing an individual's time-series, VAR first generates a multivariate model of temporal associations, which is valid for this single case only. The idiographic model represents the building block for succeeding prototypical models.

(7) Prototypical nomothetic model. After all individuals have been assessed by idiographic models, TSPA then aims to derive overarching/prototypical models of general associations between the system's variables. Prototypicality is achieved by various means of aggregation. The most parsimonious way of aggregating individual models is by averaging the standardized regression weights across individuals. Averaged regressions that significantly differ from an expected mean of zero may then be taken as indices for generalized structure in the entirety of the sample. More details on the parameters involved in this process may be found in the step-by-step procedures provided below.

VAR versus traditional methods

For a general appreciation of VAR, the cornerstone of TSPA, in comparison to more traditional methods, Table 1 outlines characteristics of four different approaches commonly used for the analysis of time series. For reasons of simplicity, we will restrict our comparison of VAR with other approaches to their common/standard usage and we will primarily comment the peculiarities of VAR.

-- Insert Table 1 around here --

Let us first consider the data requirements in terms of properties of the data set to be analyzed: Table 1 shows that VAR is particularly suited for situations where data of few or even single cases is available. However, this flexibility in terms of patients needed in a sample comes at the

price of a more demanding criterion regarding the number of data points: For every parameter included in the model, at least 5 data points should be available. Missing data cannot be handled by VAR (for more details see step-by-step instructions below), but the length of each patient's time series may vary freely. Apart from these 'logistic' requirements, the methods also differ with respect to their analytic focus: VAR focuses on individual models and trajectories, whereas other approaches mostly emphasize group-level characteristics. A major advantage of VAR models is the ability to easily include more than one dependent variable; a fact that is especially useful for psychotherapy process data, where multiple factors of a psychotherapy system can be estimated within one summary model. Recent extensions of multilevel models may also allow multivariate estimation (see e.g. Baldwin, Imel, Braithwaite, & Atkins, 2014), but the specification of multivariate associations gets rather complicated with increasing numbers of variables. The same is true for the inclusion of lagged associations: Their consideration is an integral part in VAR, whereas other approaches require the generation of lagged versions of variables. Apart from the traditional methods shown in Table 1, there are some quite specialized methods that bear similarities to VAR: One of them is dynamic factor analysis, a technique based on Cattell's (1952) *P*-Technique, which factorizes an individual's responses in the time-domain (Fisher et al., 2011; Molenaar, 1985). Recent combinations of structural equations models (SEM) with autoregressive time-series analysis extend classical SEM by taking into account the temporal associations of variables (Bollen & Curran, 2004; Hamaker et al., 2005; Oud & Jansen, 2000), and cross-lag panel analysis – an elaboration of bivariate, two time-points analyses – likewise allows quasi-causal inference (Meuret et al., 2010; Smits et al., 2012; Smits et al., 2006). Taken together, traditional ANOVA, SEM and MLM provide integrated statistics at the price of neglecting idiographic information, whereas VAR analysis provides a wealth of idiographically suitable models at the price of some stricter requirements on data collection. Viewed from a

clinical standpoint, VAR provides an intuitive summary of the way different factors in psychotherapy process interact with one another over time (i.e. time-lagged associations) and hence allows the quantitative reconstruction of the dynamics active in a therapeutic system.

Time Series Panel Analysis (TSPA)

TSPA is based on vector autoregression (VAR), which quantifies the linear dependency of a set of variables at time (t) on values of the same set at n previous points in time ($t-n, t-n+1, \dots, t-1$). This linear dependency includes both autoregressive components (i.e. components that relate to themselves over time: $X_{t-1} \rightarrow X_t$) and multivariate associations (i.e. associations between different variables over time: $Y_{t-1} \rightarrow X_t$). VAR was initially developed as a tool in econometrics (Sims, 1980; Stock & Watson, 2001), e.g. to predict the evolution of shares in economic markets. VAR accounts for interdependencies and dynamic relationships in multivariate systems and allows forecasting complex (multivariate) time series containing autoregressive elements. In the area of economic series, VAR is used to model relationships among shares and associations between external influences and the system. The application of VAR models in psychological research has been described recently (e.g. Stroe-Kunold, Gruber, Stadnytska, Werner, & Brosig, 2012; Tschacher & Ramseyer, 2009; Wild et al., 2010), and in this article, we will focus on the selection and interpretation of results, while leaving out mathematical and statistical details of VAR models, as these are detailed in the publications mentioned above. The following methodological steps may be viewed as general recommendations that apply to various statistical packages implementing VAR analyses (e.g. SAS®, R, Stata®).

Application of TSPA to ambulatory psychotherapy sessions

In this paper, our didactic goal was to provide an exemplary analysis of psychotherapy process using TSPA, by which we also explored open issues of research in a dynamic systems framework: First, we searched for temporal associations between factors of psychotherapy (alliance, self-efficacy, clarification, and mastery) in a dataset of fully monitored ambulatory psychotherapies. Second, we illuminated the relative significance of the therapists' versus the patients' contributions to the process by exploring which associations derived from the patients' or therapists' perspectives. Third, we explored associations between temporal dynamics and psychotherapy outcome.

Dataset. This empirical dataset of ambulatory psychotherapies consisted of $N = 87$ dyadic psychotherapy courses taken from a comprehensive database established at the outpatient psychotherapy clinic of the University of Bern, Switzerland. Only completed therapies with a minimum of 30 sessions were included in TSPA analyses. (Figure W1 in the supplementary online material shows the flowchart of session selection criteria).

Measures of therapeutic process. To appropriately evaluate temporal processes in psychotherapy variables, the relevant factors that contribute to change in psychotherapy have to be specified. One way to monitor these processes is by using post-session questionnaires (see supplementary online material S1 for further details). Owing to our empirically based perspective, post-session questionnaires were used that a) capture patients' interpersonal experiences in sessions (= alliance, AL_P), and b) assess patients' subjective experience of progress induced by sessions (= self-efficacy, SE_P). In line with a dynamic systems perspective, we viewed the therapy dyad as a system, which implies that we were also interested in the therapist's perspective. We therefore assessed c) therapists' interpersonal experience (= alliance, AL_T) and their specific use of both d) clarification interventions (traditionally used in

psychodynamic and humanistic therapies = clarification, CL_T) and e) mastery interventions (traditionally used in cognitive-behavioral therapies = mastery, MA_T). Versions of the *Bern Post-Session Report* (BPSR; Flückiger, Regli, Zwahlen, Hostettler & Caspar, 2010) were independently administered to patients (BPSR-P, 22 items) and therapists (BPSR-T; 27 items) after each therapy session (see supplementary online material S2 and Table W1 for details and exemplary items).

Measures of therapeutic success. Therapy outcome was assessed using a pre-to-post change measure that quantified constructive thinking (Constructive Thinking Inventory, CTI; Epstein & Meier, 1989). The CTI (46 items) measures experiential intelligence, which reflects a person's tendency to automatically think in ways relevant for solving everyday problems, by categorizing thoughts as constructive or destructive (see supplementary online material S2 for details).

Step-by-Step Procedures for TSPA (see supplementary online material, Tables W4 & W5 for SAS and R-code)

General data requirements. All procedures described in Table 1 assume that time-series have stable (time-invariant) means, variances, and autocovariances. This property is called stationarity or – when the series show a linear trend, drift or slope – the series are 'trend stationary'. The models described in this paper and most variables assessed in psychotherapy process research (e.g. alliance, symptom distress, etc.) pertain to the category of trend stationarity, because these variables are usually undergoing systematic change over the course of therapy. The VARMAX procedure implemented in SAS® version 9.3 (SAS Institute Inc., 2011) provides a simple option (trend=linear) for VAR-analyses of data that contain linear trends, and the same applies to the package *vars* (Pfaff, 2008; Pfaff & Stigler, 2013) implemented in *R* software (*R* Core Team, 2014). The code for procedures of the analyses presented here is

provided in the supplementary online material (Tables W4 & W5). Besides the assumption of stationarity, time-series analysis requires that data were assessed at fixed intervals (equally spaced data). For session-report data, this requirement is met as long as sessions are assessed regularly. The fact that the number of days between sessions may vary over the course of therapy does not necessarily violate the assumption of equally spaced data because the calculated VAR-model is based on session-to-session associations, not on exact temporal distances in terms of days between sessions. Our own experience with post-session questionnaires tells us that non-equally spaced data (e.g. due to missing or rescheduled sessions) usually lead to an underestimation of temporal effects, which implies that this is a conservative strategy (see paragraph on missing data).

Time-series length. VAR analyses require a minimal number of observations for the computations. This lower limit depends on the number of parameters (variables in the model) that a specific VAR model estimates. For illustrative purposes, we have included two different models: One analysis with i) three parameters and another, more complex analysis, where ii) five individual variables were entered into the model. At the minimal time-lag of 1, these conditions resulted in i) 9 auto- and cross-regressions (3×3) and 3 trends, i.e. 12 estimated parameters (see Figure W2, supplementary online material) and in ii) 30 estimated parameters (5×5 plus 5). The minimal number of data-points needed for these cases imposed by e.g. the VARMAX procedure in SAS would be i) 6 and ii) 13 observations; however, we recommend as a rule of thumb that the number of observations should be higher than the number of estimated parameters. In the application presented here, we chose a minimum of i) 20 and ii) 30 observations.

Missing data. The VAR computation in SAS and R will stop running when encountering missing data: One can deal with missing time-series data in various ways. One possibility is to use imputation procedures that substitute the missing data points (e.g. by the mean of the

variable in question). Depending on the chosen imputation method and the number of missing values, imputation may lead to over- or under-estimation of VAR parameters. We advocate the simpler, radical method of treating the time series as though there were no missing values. By ignoring missing values, we handle a time-series with e.g. a missing session #18 as if no gap existed between sessions #17 and #19. This strategy has the effect of mixing associations with lags higher than 1 with the lag-1 associations. Erroneously assuming lag-1 associations (#17,#19,#20) when the time between measurements was actually longer (#17,missing,#19,#20) leads to an underestimation of effects, because we empirically found that lag-2 models resulted in poorer fit in the present data (see Results section). For TSPA models in psychotherapy data, this radical method of dealing with missing data is better than the imputation method, because it is conservative and less prone to entail inflated models of change.

Step 1: Idiographic modeling.

As described in the introduction, it was not assumed that each individual series would reproduce on the group level; hence each patient's individual time-series was analyzed separately. Such a strategy provides the most appropriate model for each therapy course. The procedures in SAS and *R* yield VAR parameters that quantify sequential associations by ascription of positive, zero, or negative regression weights and *T*-values (the use of the symbol *T* is SAS-convention). These *T*-values are defined as parameter weight (= estimate of association between variables) divided by their standard error; they serve as indicators for statistical significance at the individual level. To further illustrate the importance of the idiographic modeling approach, consider the exemplary case of a single patient provided in Fig. 1, panel C.

The selection of an appropriate lag depends on theoretical considerations (e.g. session-to-session change in psychotherapy; monthly changes in product sales, etc.), or may be chosen empirically, based on information criteria (indicators of goodness of fit of a given model, such as

Akaike's Information Criterion (AIC): Akaike, 1974). Lower AIC values indicate better fit; AIC values of each model are provided by the software programs. For the aggregation of a prototypical nomothetic model, the same lag should be chosen for all idiographic models. AIC may be used to determine the most appropriate lag: One may count, for each lag, the number of models with AIC minima, and decide on the appropriate lag on the basis of a chi-square test (thus finding the lag with the highest percentage of models with lowest AIC values). Another option is to decide between two different lags by calculation of a pairwise *t*-test for dependent data on AIC values. Both chi-square and pairwise *t*-test are done outside the VAR procedures of SAS or R.

In addition to the lagged VAR computations, synchronous associations (at time *t*) between variables may be calculated. For these associations, we use the correlations between residuals at lag-0. These residuals are what remains after all other effects, such as trends, auto- and cross-correlations, have been accounted for. Correlations of residuals are superior to conventional correlations because they take into account that in each patient we are dealing with dependent measures. Correlation coefficients of residuals are transformed to Fisher's *Z*. The resulting *Z*'s can then be regarded as indicating the effect sizes of synchronous (lag-0) associations.

Tests for the evaluation of causal associations may be performed at this stage: Both SAS and R allow testing for Granger causality (see supplementary online material, Tables W4 & W5). These tests are useful especially for the analysis of single cases; in TSPA they are not commonly used in further steps.

Step 2: Statistical evaluation of effects

To statistically test individual or group-level model parameters, different strategies are available. One practical solution is to test the *T*-values of VAR parameters (i.e. the standardized

VAR parameters) according to the standard $p < .05$ criterion, i.e. a T -value of ± 1.96 and higher is considered statistically significant. For aggregated models (derived from the assemblage of individual parameters), a test against a hypothetical distribution around zero can be performed: The T -values of VAR parameters are distributed around a mean of zero in 'time series' of random numbers. Thus the null-model assumes that if no systematic associations exist in the data, the averaged T -values of individual models of a group of patients would converge to zero; additionally, positive and negative associations would cancel each other out (Tschacher & Ramseyer, 2009). Testing the significance of T -values in the group dataset is thus accomplished by comparing the group's distribution/average against the hypothesized average of zero (one-sample t -test for the mean). This tests statistical significance of the aggregated (average) T -values, which is different from the ± 1.96 criterion used in the individual case, implying that values inside the ± 1.96 interval may be considered statistically significant. T -values at the nomothetic level may also be converted into effect sizes: The sample's average T -value divided by the sample's T -value standard deviation gives an approximation of Cohen's d . A positive effect size thus denotes a (standardized) superiority of positive associations over no (zero) association.

Step 3: Nomothetic aggregation.

Once each patient's model has been estimated, aggregations are indicated when the research goal is to find nomothetic associations. The respective grouping variables may be chosen based on theory, experimental design, diagnosis, or – in the sense of a convenience sample – by aggregating the entire sample or parts thereof (e.g. according to diagnostic groups, see Tschacher et al., 2012). Aggregation is done outside of the VAR procedures in SAS or R; these data-logistic steps may be performed in any statistical software. After the individual cases have been aggregated, the group-averages of T -values can be assessed. Mean associations above

a critical threshold – such as the null hypothesis described above – are then selected for further testing, as we did in the present sample. At this point, the aggregated dataset may be supplemented with additional individual-level data: In our present example, each patient's CTI score – the measure of therapeutic success – was added for the implementation of the next step.

Step 4: Associations with outcome.

The process-outcome analyses may be based on those associations identified in Step 3, or on all available associations (e.g. Tschacher & Kupper, 2002). Depending on the structure of the dataset, multiple regression analyses or mixed model analyses may be performed. For the present analysis, we calculated a multiple regression model to explain the outcome variable 'change in constructive thinking'. The process-outcome sample was smaller than for the presented prototypical model because CTI-scores were only available in $n = 54$ patients.

Results

The focus of the results section will be restricted to the temporal aspects found in the data and to the application of TSPA. Additional background on sample data and a traditional pre-to-post analysis of CTI scores and post-session questionnaires is provided in the supplementary online material, S3 & Table W2.

Idiographic analyses. The individual VAR analyses showed that a lag-1 model provided the best overall model fit. At the level of the whole sample, corrected Akaike information criteria of lag-1 models were superior to lag-2 models [$AIC_{lag1} = -7.49$, $SD_{lag1} = 2.08$; $AIC_{lag2} = -6.34$; $SD_{lag2} = 2.34$; $t(86) = 15.45$; $p < .0001$; $d = 0.52$]. AIC superiority of lag-1 over lag-2 was found in 85 of 87 individual patients [$\chi^2(1) = 19.05$, $p < .001$].

Comments. The patient-level models derived at this first step of the analysis are usually highly heterogeneous. Depending on the research aim, they may be directly used for further

explorations, e.g. in single-case designs. In TSPA, idiographic models are assembled into a new dataset consisting of all VAR parameters and associated T -values from each patient.

Nomothetic analyses, prototypical model of change. Data of all 87 patients were aggregated to provide a prototypical model capturing the overall dynamics found across therapies (Figure 1/D). Statistical tests of T -values were based on the comparison with a hypothetical average of zero, thus average T -values indicate whether the prototypical model significantly deviated from the expected average of zero. The prototypical model was characterized by the following attributes: *Linear trends (TR)*, *systematic change over the course of therapy*. Positive linear trends were present in all variables except therapist's clarification intervention. Patient-assessed alliance and self-efficacy showed the strongest growth ($T = 1.25$ and 1.35 ; both $p < .0001$), while therapist-assessed alliance ($T = 0.50$; $p < .01$) and mastery interventions ($T = 0.58$; $p < .01$) were characterized by weaker linear trends. *Temporal stability, predictability*. The horizontal arrows in Figure 1/D (i.e. the autocorrelations of factors) of all five factors were positive, and – with the exception of therapist's rating of the alliance ($T = 0.50$; $p < .01$) – autocorrelations had high T -values ($T = 0.97$ to 1.13 ; all $p < .0001$). All five psychotherapy factors were thus characterized by significant temporal stability in the course of therapy. *In-session associations, lag-0 correlations*. The correlations between residuals within one session (lag-0) were limited to the alliance factors and self-efficacy. All three variables showed positive correlations, indicating that within a single session, a good alliance rating by the patient or the therapist was linked with high self-efficacy ($Z = .40$ and $.36$). Patient's and therapist's perspective on the alliance were moderately correlated at lag-0 ($Z = .26$). *Temporal associations between factors, mechanisms of change*. Of all possible lagged cross-regressions ($n = 20$), only two reached statistical significance. Both of these cross-factor associations resided within the patient's perspective: Patient's alliance at the previous session predicted subsequent

self-efficacy ($T = 0.39$; $p < .01$) and patient's self-efficacy predicted subsequent alliance ($T = 0.25$; $p < .05$). Alliance and self-efficacy were thus connected in a positive feedback system.

Comments. The step of aggregating idiographic models and assessing statistical significance and/or effect sizes of the prototypical model is the most important feature of TSPA: The researcher has a wide range of choices regarding the way aggregation should proceed. When no a-priori hypotheses were generated prospectively, we recommend the simple group-aggregation demonstrated above. Depending on the dataset available, other criteria may be used. One option is presented below, where we explored differences between phases of therapy.

Temporal evolution of VAR models. We computed additional VAR models in order to compare initial and final phases, i.e. the first and last 20 sessions of therapies. Owing to the smaller number of 20 time-points, only three variables were included in these VAR models (AL_P , SE_P , AL_T). The inclusion of 20 sessions entailed overlapping phases in those $n = 37$ therapies with less than 40 sessions. This partial overlap leads to a conservative (under-) estimation of differences. The most striking difference between phases is the complete lack of auto- and cross-correlations in the final phase (see Figure W2, supplementary online material). In the initial phase of therapy (first 20 sessions of each patient), patient's alliance is autocorrelated ($T = 0.40$; $p < .01$) and positively influences both subsequent self-efficacy ($T = 0.47$; $p < .001$) and subsequent therapist's alliance ($T = 0.32$; $p < .05$). Self-efficacy and therapist's alliance are not autocorrelated, and the lag-0 correlations among all three variables are moderate ($Z = .26$ to $.44$). In the final phase of therapy (last 20 sessions), there are no significant auto- or cross-correlations. Trends are slightly lower and lag-0 correlations are similar to those of the initial phase.

Comments. The temporal distinction of initial versus final phases of therapy demonstrates that the choice of the reference frame for VAR models has to be made with careful reflection.

Theoretical and practical considerations should guide this decision.

Process-outcome analysis. The analysis of associations with outcome (multiple regression analyses with CTI effect-size as dependent variable) was based on all available VAR parameters and trends (in total, $n = 30$ parameters as predictors). Lag-0 associations were not included in the regression model because the temporal aspects (captured by VAR parameters) were the main focus of interest. The resulting multiple-regression model explained $R^2 = 37.3\%$ of the variance [$F(30, 53) = 2.05$; $p = .040$; $\eta^2 = 0.728$]. Seven VAR parameters significantly predicted change in CTI-scores (see Figure 2), and the majority of these associations originated from the two intervention strategies reported by the therapists (see also Table W3, supplementary online material).

-- Insert Figure 2 around here --

Linear trends (TR): The linear trend of patient's self-efficacy was positively associated (standardized $\beta = .42$) with change in constructive thinking: Patients with pronounced linear increase of self-efficacy over the course of therapy also had high change-scores in CTI.

Temporal stability: The autocorrelation of both therapist's clarification and mastery interventions ($\beta = .40 / .36$) were associated with the CTI score: Therapies with higher predictability of therapist's interventions had higher gains in constructive thinking. *Temporal associations*

between factors: CTI outcome was higher when the following associations were enhanced:

Therapist's alliance associated with subsequent alliance ratings of patients ($\beta = .56$); clarification interventions associated with subsequent self-efficacy ($\beta = .61$); mastery associated with subsequent patient's alliance ($\beta = .80$) and with therapist's clarification interventions ($\beta = .46$).

Comments. In terms of increase of knowledge, the process-outcome associations are probably the

most interesting parts that may be achieved by TSPA. This combination of temporal dynamics (gained through VAR, 'distilled' by TSPA to a prototypical model) with traditional outcome measures enables researchers to fully combine the benefits of time-series analyses with pre-to-post change assessments. In the present demonstration, the association of temporal stability in therapist's intervention strategies with better outcome may be seen as a step towards an enriched assessment of process-outcome relationships.

Discussion

This article provides an empirical demonstration of TSPA in a dataset of ambulatory psychotherapy cases. Using five factors that describe a therapeutic system session by session throughout therapy, TSPA allows identifying a prototypical model of change. This methodology enables process research to address questions concerning a) the temporal dynamics of process factors, b) the respective contributions of patients and therapists, and c) the associations between mechanisms of change and therapy outcome. This was exemplified in 87 psychotherapies. In the prototypical model of this dataset, all five factors showed temporal stability (autocorrelation) and the two patient factors alliance and self-efficacy were connected in a positive feedback loop. Furthermore, TSPA elucidated that those therapies were more successful in whom therapist's interventions enhanced subsequent alliance and self-efficacy of patients. Most importantly, the process-outcome analysis pointed to a previously overlooked facet of therapists' intervention strategies: Temporal stability. TSPA uncovered that the autocorrelation of therapists' clarification and mastery interventions was associated with improvement in patients' constructive thinking. This finding implies that patients evidenced higher changes in their thinking style when they engaged with therapists who did not much change the intensity of their interventions from one session to the next ($t-1$ to t). In line with this interpretation was the

finding that low temporal stability (autocorrelation) was not confounded with low dosage: The levels of clarification and mastery interventions were unrelated to change in constructive thinking ($r = -.04 / .05$; see Table W1 / W2, supplementary online material). Taken together, these results suggest that it is not the dosage of interventions, but rather the stability of therapist's interventions on a session-to-session basis that turned out to be predictors of favorable outcome.

The discussed findings are relevant insofar as neither the averages of factors nor their simultaneous associations were indicative of therapeutic improvement. Only through uncovering temporal dynamics assessed by TSPA it was possible to clarify the linkage of process and outcome in these therapeutic systems with differing success rates. In summary, the findings support a specific methodological contribution of TSPA to psychotherapy research.

Clinical implications: Session-to-session response of patient's factors to therapist's interventions was strongly associated with outcome: Specific short-scale effects (at the session-to-session level) may be predictive of therapy outcome and may indicate the adequacy of current therapeutic strategies. In the present dataset, lower stabilities of therapists' intervention strategies were associated with poorer outcome: This may either reflect a property pertaining to the patient – e.g. a lack of responsiveness to interventions – or a property of the therapist, e.g. excessive changing of therapeutic strategies and frequent switching of focus between mastery and clarification interventions. While it may be an adequate strategy to be sensitive to patients' early change trajectories (Stulz, Lutz, Leach, Lucock, & Barkham, 2007), therapists may actually fare better not varying their strategies too early or too often. Future studies should address these (putative) causal mechanisms by experimental designs.

Limitations. Longer therapies were overrepresented in the present study, as the minimal therapy duration was set to $n = 30$. Correspondingly, the sample contained slightly more severe cases as evidenced by initial CTI scores and CTI-change. It should thus be borne in mind that our

findings may not generalize to shorter therapies with higher proportions of less severe cases.

TSPA assumed that the VAR parameters of a single patient would not vary systematically during the course of therapy. One may challenge this assumption because change mechanisms in the initial stages of therapy may differ from those in the final stages of therapy (see Figure W2, supplementary online material). This type of problem is inherent to time-series modeling in general; the significance and stability of results may justify the chosen time frame.

General Conclusion

The purpose of this article was to explore time series panel analysis (TSPA) as a complementary method to study change processes in psychotherapy time-series data.

In the exemplary sample presented here, temporal characteristics of therapy factors explained the associations with constructive thinking better than average levels ('dosages') of factors. Being able to model such associations and to statistically assess their effect can inform researchers and clinicians alike of temporal processes in psychotherapy. This peculiarity is a core feature distinguishing TSPA from more conventional procedures. TSPA's middle ground between idiographic and nomothetic designs thus has specific merits for the psychotherapy research agenda. The implementation of TSPA in software packages such as SAS and *R* is straightforward and requires no additional programming. The broad range of applicability in time-series data, and the availability of appropriate tools, may invite and encourage researchers to a) assess psychotherapy process with a focus on temporal evolution, and b) investigate the temporal mechanisms of change in psychotherapy.

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Table 1. Overview of Various Analysis Methods Used For Psychotherapy Time-Series.

Method	Properties of data set				Analytic focus on ...		
	Few subjects	Short TS	Missing data	Varying TS lengths	Idiographic modeling	Multivariate estimation	Temporal dynamics
VAR	+	–	–	+	+	+	+
ANOVA	–	+	–	–	–	–	–
MLM	–	+	+	+	+	–	+
SEM	–	+	–	+	–	+	+

VAR = Vector Auto Regression; ANOVA = Analysis of Variance; MLM = Multilevel

Modeling; SEM = Structural Equation Modeling; TS = Time Series

+ = possible/advantage; – = impossible/disadvantage

Figure 1

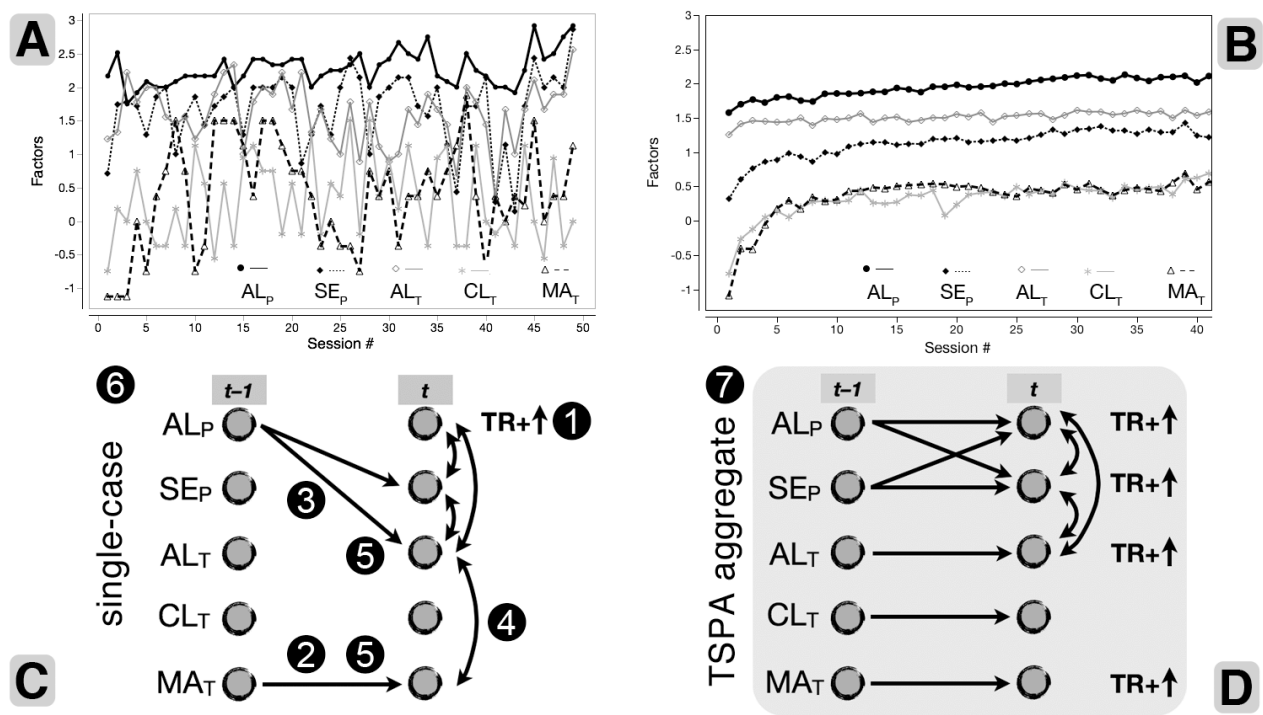


Figure 2

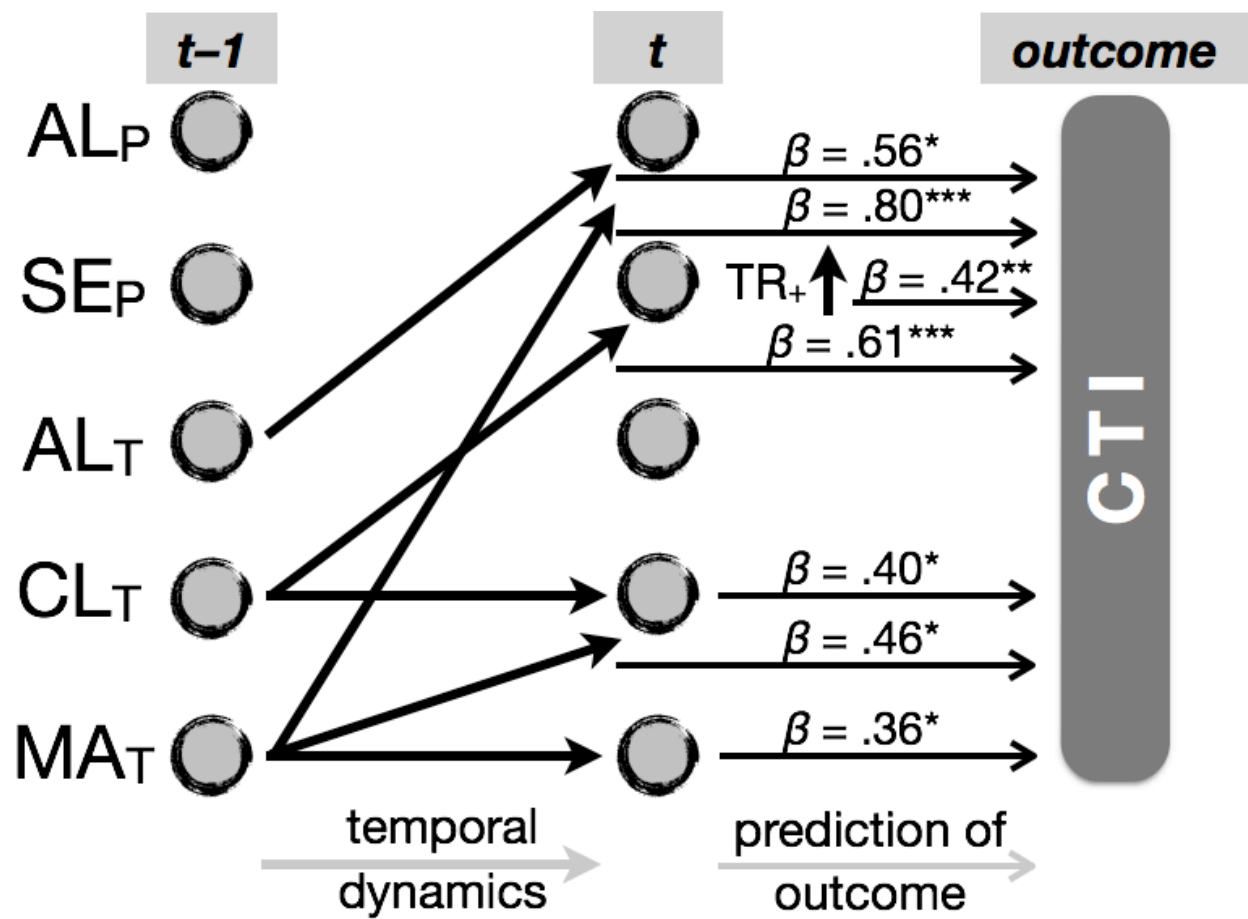


Figure 1. **A:** Time series of post-session questionnaire factors from a single case. **B:** Averaged time series ($N = 87$). Only the first 40 sessions are shown. **C:** Single case model of exemplary case depicted in panel A. **D:** Aggregated prototypical model of ($N = 87$) individual VAR models. AL_P = alliance patient; SE_P = self-efficacy patient; AL_T = alliance therapist; CL_T = clarification interventions therapist; MA_T = mastery interventions therapist. $TR_{+/-}$ = linear trend of variable. Key concepts of time-series analysis are indicated by numbers 1 to 7 (1 = Trend; 2 = Autoregression; 3 = Cross-regression; 4 = Synchronous associations; 5 = Causal inferences; 6 = Idiographic model; 7 = Prototypical nomothetic model).

Figure 2. Process-outcome associations of VAR parameters (temporal dynamics) with CTI change scores (effect sizes of pre-to-post change).

AL_P = alliance patient; SE_P = self-efficacy patient; AL_T = alliance therapist; CL_T = clarification interventions therapist; MA_T = mastery interventions therapist; $TR_{+/-}$ = linear trend of variable; β = Standardized beta of multiple regression analysis.

* $p < .05$; ** $p < .01$; *** $p < .001$